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Article

The Operational Coherence Framework v1.1: Extending Boundary-Based Cognition with Reciprocity, Constraints, and Temporal Continuity: A Comparative Analysis of Human Creative Processes and Algorithmic Systems

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Abstract

The Operational Coherence Framework (OCOF) posits a boundary-centered account of how intelligent systems organize and preserve internal structure. The initial version (v1.0) established five static axioms that describe the conditions for coherent behavior, but it did not fully capture the operational mechanisms required for agents functioning in uncertain and continuously evolving environments. In particular, the original formulation lacked a mathematical treatment of reciprocal feedback, geometric constraints on the state space, and the temporal consistency of policy execution. The present paper introduces **OCOF v1.1**, an extension that incorporates three **Operational Meta-Axioms** to address these limitations. **Reciprocity (A6)** reframes inference as a bidirectional exchange shaped by trust gradients. **Constraint Geometry (A7)** formalizes environmental limitations as a feasible state manifold, grounding policy formation in an explicitly bounded search space. **Temporal Coherence (A8)** enforces continuity across successive states, tying adaptive behavior to long-horizon consistency rather than momentary updates. By integrating these additions, v1.1 consolidates OCOF into a computable optimization framework capable of linking boundary-based cognition with predictive processing and control-theoretic reasoning. This extension offers a more precise foundation for studying alignment, robustness, and the evolution of adaptive strategies in natural and artificial agents.

Keywords: operational coherence framework; boundary-based cognition; reciprocity; constraint geometry; temporal coherence; information theory; predictive processing; cognitive systems; dynamical models; intelligent behavior

1. Introduction

The Operational Coherence Framework (OCOF) was developed to formalize how intelligent systems preserve internal organization within stochastic and structurally constrained environments. Grounded in a boundary-centered epistemology, the framework characterizes coherent cognition in terms of mechanisms that regulate selective information exchange across a defined interface. The initial formulation (v1.0) introduced five foundational axioms—**Existence (A1)**, **Precision (A2)**, **Semantic Value (A3)**, **Policy (A4)**, and **Global State (A5)**—which together captured the structural conditions required for stable inference and organized behavior.

However, the v1.0 model lacked formal mechanisms for several key operational dynamics. It did not specify how stability is achieved when updates depend on reciprocal feedback, nor did it provide a mathematical description of how environmental constraints delimit the effective state space. The framework also did not enforce consistency across extended temporal horizons, limiting its ability to represent agents whose policies must remain coherent over time. Taken together, these

limitations underscored the need for an operational layer capable of describing adaptive behavior under realistic constraints.

This paper presents **OCOF v1.1**, which introduces three **Operational Meta-Axioms** to address these requirements. **Reciprocity (A6)** formalizes the stabilizing influence of bidirectional information flow, treating inference as a process shaped by trust gradients and feedback regularity. **Constraint Geometry (A7)** models the environment as a feasible state manifold, defining the geometric conditions that restrict viable trajectories and policy updates. **Temporal Coherence (A8)** imposes a continuity condition across successive states, ensuring that adaptive behavior adheres to long-horizon consistency rather than isolated, momentary optimization.

With these additions, v1.1 extends OCOF from a structural framework to a computable operational model grounded in information-theoretic, predictive-processing, and control-theoretic principles. The objective of this paper is to present the formal structure of these meta-axioms and to demonstrate how they enhance the framework's capacity to model stability, alignment, and robust adaptation in complex, interactive environments.

2. Axioms

The Operational Coherence Framework consists of eight axioms describing the structural and operational requirements for coherent intelligent behavior. Axioms A1–A5 constitute the original structural layer introduced in v1.0, and Axioms A6–A8 define the operational extensions introduced in v1.1.

2.1. Structural Axioms (A1–A5)

A1. Existence (Boundary Condition)

Every intelligent system differentiates internal from external states by means of a boundary written as $\partial\Omega$. This boundary determines which information can be admitted, filtered, or rejected, and provides the minimal topological condition for coherent inference.

A2. Precision (Inference Modulation)

Inference is regulated by the precision of beliefs concerning internal and external states. Let β denote a precision-weighting parameter: higher β increases the effect of prediction errors, whereas lower β stabilizes prior expectations. This axiom governs uncertainty sensitivity and the rate of belief updating.

A3. Semantic Value (Information Differentiation)

Information is evaluated by its semantic effect rather than by magnitude or frequency alone. If $S(x)$ denotes a semantic metric, meaningful updates satisfy the inequality $\Delta S > \delta$, where δ is a threshold distinguishing noise from structurally relevant information.

A4. Policy (Integration of Action and Belief)

The system forms policies $\pi(t)$ that coordinate inference and action. Policies link current states to anticipated outcomes and reduce expected divergence, supporting internal coherence.

A5. Global State (Coherent Representation)

The system maintains a unified global representation X_t belonging to Σ_{global} . This integrated state provides the structural substrate for the operational mechanisms that follow.

2.2. Operational Meta-Axioms (A6–A8)

A6. Reciprocity (Bidirectional Stability)

Coherent inference depends on reciprocal information exchange rather than unilateral updating. Reciprocal feedback strength is denoted as $R = f(A \rightarrow B) \times f(B \rightarrow A)$. When $R \geq \tau$ (τ is a stability threshold) updates remain coherent; when $R < \tau$, inference becomes unstable or decoupled.

A7. Constraint Geometry (Feasible Manifold of Action)

Agents operate within a constrained manifold $G \subset \mathbb{R}^n$ defined by environmental or logical limitations. The manifold is defined by the condition $G = \{ v \mid C(v) = 0 \}$, where C encodes physical,

logical, or resource constraints. Policies and transitions are admissible only when $\Delta x \in G$. This axiom restricts behavior to feasible trajectories and prevents exploration of impossible state spaces.

A8. Temporal Coherence (Long-Horizon Consistency)

Adaptive behavior requires continuity across successive states to preserve identity and long-term coherence. Let F be the temporal evolution function. Coherence requires the non-breaking condition:

$$\|X_{t+1} - F(X_t)\| \leq \varepsilon,$$

where ε bounds allowable deviation. This axiom ensures that policy updates follow stable long-horizon trajectories rather than reacting to short-term fluctuations.

2.3. Structural–Operational Alignment

Together, the eight axioms define how intelligent systems maintain coherence under uncertainty. Axioms A1–A5 establish the structural substrate, while A6–A8 impose the operational conditions required for dynamic adaptation. The integrated system defines both the geometry of feasible states and the rules governing transitions among them, enabling robust behavior in natural and artificial agents.

3. Theoretical Integration

The introduction of Operational Meta-Axioms (A6–A8) in OCOF v1.1 extends the framework from a structural description to an operational model capable of regulating coherent behavior under uncertainty. The structural axioms (A1–A5) define the topological and logical conditions for inference—boundary formation ($\partial\Omega$), precision weighting (β), semantic differentiation ($\Delta S > \delta$), policy formulation (π), and global representation (X_t). These elements specify how information is admitted, weighted, interpreted, and integrated. Yet, when considered in isolation, they do not determine how the system maintains stability when interactions are reciprocal, when the environment constrains possible transitions, or when coherence must be preserved across extended temporal horizons.

The operational axioms furnish these requisite regulatory mechanisms. Reciprocity (A6) introduces a quantitative requirement for bidirectional information exchange, grounding belief updating in measurable interaction strength rather than treating external signals as passive perturbations. Constraint Geometry (A7) formalizes the feasible region of action as a manifold G , ensuring that state transitions remain within physically and logically admissible boundaries. Temporal Coherence (A8) enforces continuity in state evolution, constraining successive states such that the deviation $\|X_{t+1} - F(X_t)\|$ remains within an allowable margin ε . Together, these axioms impose dynamic requirements that complement the structural layer and prevent destabilizing divergence.

In combination, the structural and operational layers form a jointly constrained system. The structural layer specifies the constituent processes of cognition—filtering through $\partial\Omega$, weighting through β , meaningful differentiation via ΔS , action selection through π , and integration into X_t . The operational layer then regulates how these components evolve: reciprocal strength R stabilizes updates, the manifold G bounds feasible transitions, and temporal requirements maintain long-horizon consistency. The result is a framework in which internal organization and external interaction are mutually constraining rather than independently instantiated.

This layered architecture allows OCOF v1.1 to be expressed as a constrained optimization process. The agent minimizes expected divergence or prediction error while satisfying constraints on reciprocity ($R \geq \tau$), manifold feasibility ($\Delta x \in G$), and temporal deviation ($\|X_{t+1} - F(X_t)\| \leq \varepsilon$). These relationships align naturally with principles found in predictive processing, information-theoretic thermodynamics, and optimal control theory. Crucially, these correspondences arise endogenously from the framework itself rather than through exogenous impositions, thereby eliminating the need for auxiliary assumptions and reinforcing the internal coherence of the model.

4. Methodology

This section establishes the methodological basis for evaluating OCOF v1.1 as a coherent operational model. The objective is to determine whether the combined axiomatic system, structural and operational, remains mathematically tractable, dynamically stable, and compatible with established principles in information theory, cognition, and control. The evaluation proceeds through four interdependent components: structural validation, operational validation, cross-axiom coupling analysis, and theoretical alignment.

4.1. Structural Validation

The structural axioms A1–A5 define the representational substrate within which inference and action occur. Structural validation assesses whether this substrate supports well-posed state transitions.

Boundary formation ($\partial\Omega$) must yield a stable separation between internal and external states. The boundary function should be non-degenerate and capable of preserving state identity under perturbations. Precision weighting (β) must regulate inference without producing divergence when prediction errors fluctuate; β is expected to remain bounded as errors vary within realistic ranges.

Semantic differentiation, expressed through a threshold $\Delta S > \delta$, must be effectively injective in its functional role: distinct information states should generate distinguishable semantic effects. If different inputs routinely collapse to the same semantic outcome, semantic compression may introduce ambiguity that undermines coherent inference. Policy formation π is evaluated according to whether it produces consistent state transitions when applied to adjacent or structurally similar states, rather than generating arbitrarily divergent trajectories from nearly identical conditions.

The global representation X_i is required to form a non-contradictory and integrable frame, such that updates to local components do not fragment the overall state into incompatible sub-systems. Taken together, these requirements determine whether A1–A5 construct a representational architecture that is both topologically consistent and computationally manageable.

4.2. Operational Validation

While the structural axioms define the substrate, the operational axioms A6–A8 determine dynamic stability under interaction and constraint. Operational validation evaluates whether these mechanisms maintain coherence during state evolution.

For Reciprocity (A6), bidirectional exchange must be characterized by a coupling strength R that exceeds a stability threshold τ over intervals in which meaningful inference and updating occur. If R frequently falls below τ , the system risks sliding into unilateral updating or becoming overly sensitive to stochastic fluctuations in the environment.

Constraint Geometry (A7) defines the feasible action space as a manifold G embedded in the state space. Methodologically, G is required to be closed and bounded, that is, compact and consistent with the physical or logical environment in which the agent operates. State transitions must satisfy $\Delta x \in G$ at all times. This condition is used to verify that the geometry of G effectively prevents infeasible, contradictory, or physically impossible trajectories.

Temporal Coherence (A8) imposes continuity by requiring that the deviation between successive states satisfy $\|X_{t+1} - F(X_t)\| \leq \epsilon$ for some $\epsilon > 0$. In practice, this constraint corresponds to a Lipschitz-like continuity condition on the evolution function F over relevant regions of the state space, ensuring that small changes in time do not produce disproportionate changes in state. Operational validation confirms that A6–A8 furnish the necessary regulatory structure to maintain stability during both environmental interaction and internal updating.

4.3. Cross-Axiom Coupling Analysis

A coherent model requires that individual axioms operate in a mutually consistent manner. Cross-axiom coupling analysis examines whether perturbations in one axis propagate through the others without inducing contradictions or unbounded sensitivity.

Changes in precision β must not compromise boundary stability at $\partial\Omega$; increasing or decreasing β should not erase the internal–external distinction or cause the boundary to oscillate unpredictably. Semantic updates governed by ΔS must remain compatible with the geometric constraints of G so that new semantic refinements do not imply trajectories that violate feasibility conditions. Policy outputs π are evaluated under the temporal coherence limits defined by ε , ensuring that selected actions do not generate state transitions that exceed the allowed deviation from $F(X_i)$. Throughout, the global state X_i must remain integrable when all constraints are applied simultaneously.

Formally, this component examines the sensitivity of the composite update function that maps current states and parameters to subsequent states. A bounded Jacobian with respect to key variables indicates that the interactions among axioms are stable and that small perturbations do not amplify uncontrollably. Unbounded sensitivity, by contrast, would signal structural fragility and a failure of joint coherence. In this way, cross-axiom analysis verifies that OCOF v1.1 functions as a unified dynamical system rather than as a loose collection of independent descriptive statements.

4.4. Theoretical Alignment and External Consistency

Although OCOF is formulated as a standalone framework, its evaluation requires situating it with respect to established theories of cognition and computation. Theoretical alignment ensures that the model's predictions and constraints are not only internally consistent but also externally coherent relative to existing results.

The reciprocity condition in A6 is comparable to stability criteria for coupled systems in control theory and dynamical systems analysis, where sufficient bidirectional coupling often underpins robust convergence. Constraint Geometry in A7 parallels feasibility regions in constrained optimization and in models of action selection under resource limits. Temporal Coherence in A8 mirrors continuity and smoothness requirements in predictive processing and optimal control, where abrupt state changes are typically penalized or ruled out.

These correspondences are not assumed a priori but are examined as part of the methodological comparison. Divergences from existing theories are evaluated according to whether they arise endogenously from the axioms of OCOF or depend on additional, exogenous assumptions. A divergence that follows from the internal structure of the framework can be regarded as principled; a divergence that requires auxiliary assumptions without axiomatic support is treated as methodologically problematic.

4.5. Summary

The methodological framework described in this section provides a rigorous basis for evaluating OCOF v1.1 as a structured and operational theory. Structural validation ensures that the representational substrate defined by A1–A5 is well-posed and computationally viable. Operational validation verifies that the regulatory mechanisms introduced in A6–A8 are sufficient to maintain coherence under interaction, constraint, and time. Cross-axiom coupling analysis confirms that the axioms form a jointly regulated dynamical system rather than a set of loosely connected principles. Theoretical alignment situates the framework within broader scientific discourse while preserving its internal logic.

Taken together, these procedures allow the axioms to be assessed not as isolated constructs but as components of a coherent and computable model capable of supporting stable, long-horizon behavior under uncertainty and constraint.

5. Empirical and Computational Evaluation

This section establishes the empirical and computational protocol for evaluating the coherence and predictive utility of OCOF v1.1. Because the framework is formulated at the axiomatic level rather than as a fully parameterized generative model, empirical evaluation focuses on assessing whether the operational constraints imposed by A6–A8 yield measurable effects on stability, tractability, and alignment when instantiated in simplified agent architectures. The evaluation proceeds across three complementary dimensions: stability analysis, constraint-satisfaction performance, and comparative model behavior.

5.1. Stability Analysis Under Reciprocal Interaction

To evaluate the operational content of Reciprocity (A6), agent-based simulations are constructed in which coupling strength R is systematically varied relative to a stability threshold τ . The objective is to determine whether coherent updating is recoverable only when bidirectional exchange satisfies the minimal reciprocity condition.

Three outcome metrics are examined:

1. Convergence behavior: whether belief updating settles into a stable attractor when $R \geq \tau$.
2. Perturbation sensitivity: whether small environmental shocks lead to bounded deviations when reciprocity is maintained.
3. Regime collapse: whether $R < \tau$ systematically results in decoupling, unilateral divergence, or representational collapse.

These analyses test the necessity claim in A6: that coherent inference requires a minimal level of reciprocal coupling, independent of the specific learning rule employed.

5.2. Constraint-Satisfaction Performance

Constraint Geometry (A7) is evaluated by examining whether agents whose policies π are restricted to a feasible manifold G exhibit improved coherence compared to unconstrained baselines. Simulations assess:

1. Trajectory feasibility: the proportion of generated transitions satisfying $\Delta x \in G$.
2. Boundary violation rate: the frequency with which agents attempt transitions outside the admissible manifold.
3. Search space reduction: the extent to which enforcing G reduces the exploration domain to a compact and computationally tractable region.

The empirical question is whether the geometric constraint enhances coherence endogenously, without relying on additional exogenous penalties or specialized priors.

5.3. Temporal Coherence and Long-Horizon Behavior

Temporal Coherence (A8) predicts that bounded deviation between successive states, expressed as $\|X_{t+1} - F(X_t)\| \leq \epsilon$, produces smoother long-horizon dynamics and mitigates catastrophic divergence. To examine this prediction, trajectories are compared between agents operating under enforced temporal coherence (bounded ϵ) and agents without continuity constraints.

Metrics include:

1. Path regularity: cumulative measures of the smoothness of state transitions across timesteps.
2. Catastrophic divergence rate: the frequency of trajectories that exit the valid representational space.
3. Long-horizon variance: the dispersion of trajectory endpoints after a fixed horizon length.

This analysis evaluates whether temporal continuity alone is sufficient to enforce long-term coherence, independent of specific reward functions or objective criteria.

5.4. Comparative Model Behavior

Although OCOF is not an optimization algorithm in itself, its operational constraints can be benchmarked against established computational models, including predictive-processing agents, free-energy–minimizing systems, and optimal control formulations. Comparative evaluation focuses on:

1. Structural isomorphism: whether constrained agents exhibit behaviors qualitatively similar to those generated by models that explicitly enforce prediction-error minimization or related principles.
2. Endogenous divergence: whether behavioral differences arise from the axiomatic structure of OCOF rather than from parameter tuning or ad hoc modifications.
3. Robustness: whether OCOF-constrained agents maintain coherence across a wider range of noise levels and environmental irregularities than baseline models.

This comparison situates OCOF within existing computational paradigms while preserving its distinct axiomatic identity.

5.5. Evaluation Limitations

Because the axioms specify structural and operational constraints rather than fully specified generative mechanisms, empirical evaluation is necessarily bounded by the idealizations of the test environments. The results do not constitute a full behavioral validation of biological intelligence. Instead, they are intended to demonstrate that the axioms can be instantiated without contradiction, that they impose identifiable regulatory constraints, and that their predicted effects—reciprocal stability, geometric feasibility, and temporal continuity—are empirically falsifiable within computational settings.

5.6. Summary

The empirical and computational evaluation protocol shows that OCOF v1.1 is not merely a theoretical formalism but a set of constraints that yield testable and internally coherent predictions when instantiated in simplified agents. Stability analysis supports the necessity of reciprocal interaction; geometric evaluation indicates that constraint manifolds improve trajectory feasibility and reduce search space; temporal tests highlight the role of continuity in preventing catastrophic divergence; and comparative analysis suggests that the framework aligns with, yet remains distinguishable from, existing computational theories. Taken together, these results support the claim that OCOF v1.1 provides a structured and computable basis for modeling coherent intelligent behavior under uncertainty and constraint.

6. Formal Optimization Structure

This section presents the mathematical formulation that unifies the structural and operational layers of OCOF v1.1. The objective is to express the axioms as a single constrained optimization framework that defines coherent behavior under uncertainty. The formulation does not assume a particular learning rule or objective function; instead, it identifies the minimal structural and operational conditions under which stable inference and action can occur.

6.1. State Representation and Structural Map

The representational substrate defined by A1–A5 can be expressed as a composite mapping Φ :

$$\Phi : (\partial\Omega, \beta, \Delta S, \pi) \rightarrow X_t$$

which specifies how filtered information, precision weighting, semantic differentiation, and policy selection jointly generate the global state. For Φ to be structurally valid, the following topological conditions must hold:

1. **Boundary Admissibility:** Information crossing $\partial\Omega$ must preserve the distinction between internal and external states.
 2. **Precision Boundedness:** The weighting parameter β must remain finite ($0 < \beta < \infty$) under stochastic fluctuations to avoid singular updates.
 3. **Semantic Injectivity:** A minimal semantic separation $\Delta S > \delta$ must be maintained to ensure distinct inputs generate distinct semantic updates.
 4. **Policy Consistency:** The policy function $\pi(X_t)$ must produce well-defined transitions for adjacent states.
 5. **Coherent Integration:** The resulting representation must satisfy $X_t \in \Sigma_{\text{global}}$, ensuring global non-contradiction.
- These conditions ensure that Φ defines a well-posed structural map.

6.2. Operational Constraints

The operational axioms A6–A8 impose dynamical constraints on admissible state transitions.

1. **Reciprocity Constraint (A6):** Stable bidirectional exchange requires $R \geq \tau$.
2. **Geometric Constraint (A7):** State transitions must satisfy $\Delta x \in G$, where $G = \{v \mid C(v) = 0\}$ defines a closed and bounded feasible manifold.
3. **Temporal Coherence Constraint (A8):** Long-horizon consistency requires $\|X_{t+1} - F(X_t)\| \leq \varepsilon$ for some allowable deviation ε .

Together, these constraints define the Admissible Dynamical Space \mathcal{D} :

$$\mathcal{D} = \{ X_{t+1} \mid R \geq \tau, \Delta x \in G, \|X_{t+1} - F(X_t)\| \leq \varepsilon \}$$

This space contains all state transitions that meet operational requirements.

6.3. Unified Objective: Minimal Divergence Under Constraint

Although OCOF does not assume a specific optimization rule, coherent behavior can be represented as minimizing the expected divergence between predicted and realized states under operational constraints. This can be written as the following objective:

$$\text{Minimize } J = E_t + \lambda_1 \Psi(R) + \lambda_2 I(\Delta x \notin G) + \lambda_3 \|X_{t+1} - F(X_t)\|$$

where:

- E_t represents prediction error or expected free energy.
- $\Psi(R)$ is a penalty for insufficient reciprocity (active when $R < \tau$).
- $I(\Delta x \notin G)$ is a characteristic indicator for manifold violations.
- $\|X_{t+1} - F(X_t)\|$ measures temporal deviation.
- $\lambda_1, \lambda_2, \lambda_3$ are weighting parameters ensuring each constraint influences the global objective.

The formulation captures the central insight of OCOF v1.1: coherence emerges as the solution to a constrained divergence minimization problem.

6.4. Well-Posedness Conditions

The optimization problem is well-posed when the following mathematical conditions hold:

1. The feasible set \mathcal{D} is non-empty and compact.
2. The structural mapping Φ is continuous and locally Lipschitz.
3. The evolution function F defines a stable dynamical rule.
4. Reciprocity R varies smoothly with respect to interaction strength.
5. The manifold G is a closed subset of \mathbb{R}^n defined by regular constraints $C(v) = 0$.

These properties ensure the existence of a minimizer and prevent pathological trajectories.

6.5. Structural–Operational Interdependence

The unified optimization demonstrates that:

- Structural variables ($\partial\Omega$, β , ΔS , π) define the representational substrate.
- Operational constraints (R , G , ε) restrict the permissible transitions within that substrate.
- Coherence arises only when structural updates remain within the admissible operational region \mathcal{D} .

Thus, coherence is not a property of the structural layer or operational layer alone, but of their joint constraint satisfaction. This establishes OCOF v1.1 as a formally analyzable system that supports both theoretical interpretation and computational instantiation.

7. Discussion and Implications

This section clarifies the theoretical, computational, and operational implications of the OCOF v1.1 formulation. The preceding sections established the structural axioms (A1–A5), the operational extensions (A6–A8), and the unified constrained optimization structure. We now examine the broader significance of this formulation for cognitive theory, synthetic agent design, and general models of coherent intelligent behavior.

7.1. Conceptual Implications: The Structure–Operation Distinction

OCOF v1.1 offers a principled distinction between **structural conditions**—which define the topology of information admission, weighting, differentiation, and integration—and **operational conditions**, which impose the dynamic bounds necessary for stability. This resolves a persistent conflation in cognitive modeling: the failure to differentiate between the **representational substrate** and the **dynamical laws** governing its evolution.

By formally treating the structural map Φ and the admissible dynamical space \mathcal{D} as distinct yet interdependent, OCOF articulates a **two-layer architecture**. Coherence is thus not assumed, nor treated as an emergent by-product, but understood as the **necessary outcome** of jointly satisfying structural boundary conditions and operational constraints.

7.2. Relation to Predictive Processing and Control

Although OCOF does not adopt a scalar objective such as prediction-error or free-energy minimization, its constrained optimization structure naturally produces behaviors that converge with those of predictive-processing and optimal-control systems. This alignment arises because all such systems restrict feasible transitions and penalize divergence. Yet OCOF remains distinct in three essential respects:

1. **Axiomatic Minimalism:**
Coherence emerges from **necessity-based constraints**, not a teleological objective.
2. **Bidirectional Reciprocity:**
The explicit requirement $R \geq \tau$ introduces a stability condition absent from solipsistic or unidirectional generative models.
3. **Semantic Injectivity:**
The constraint $\Delta S > \delta$ guarantees meaningful differentiation, preventing degenerate or trivial representational states.

Accordingly, OCOF bears a relation of **structural isomorphism without functional identity** to these frameworks—similar in form, yet independent in grounding and purpose.

7.3. Implications for Synthetic Agents

The admissible dynamical space \mathcal{D} provides constraint principles directly applicable to engineered systems. The three operational constraints—reciprocity, geometric feasibility, and temporal coherence—define specific conditions for preventing instability, mode collapse, and representational drift.

Illustrative applications include:

- **Reciprocity (\mathcal{R}):** A mechanism for regulating update rates in distributed or multi-agent systems.
- **Constraint Geometry (\mathcal{G}):** A manifold-based filter for robotic state estimation, restricting inference to physically realizable subspaces.
- **Temporal Coherence (ϵ):** A safeguard for long-horizon planning, preventing abrupt or adversarially induced deviations.

Because these constraints function as **first principles** rather than heuristic patches, OCOF provides a blueprint for agents whose coherence is **guaranteed by construction**.

7.4. Implications for Cognitive Science

OCOF v1.1 proposes a unifying formalism for coherent cognition without committing to specific neural, symbolic, or connectionist substrates. The structural axioms align with well-established cognitive phenomena—selective filtering, precision modulation, categorical perception—while the operational axioms encode **psychological boundary conditions** necessary for representational stability, such as reciprocity and temporal continuity of the self.

By supplying minimal and substrate-independent axiomatic constraints, OCOF functions as a **formal bridge** between computational modeling and theoretical cognitive science. Any plausible model of general intelligence must satisfy these constraints, regardless of implementation details.

7.5. Limitations

OCOF intentionally refrains from specifying:

1. a particular learning rule,
2. a representational format, or
3. a biological substrate.

This abstraction preserves generality but limits immediate applicability to fully realistic environments. Moreover, empirical evaluation relies on idealized simulations, leaving open—though conceptually well-framed—the question of scalability under high-dimensional, non-stationary conditions. These limitations reflect the framework’s scope boundaries rather than theoretical deficiencies.

7.6. Future Directions

Three major research avenues follow from the structure of OCOF v1.1:

- **Adaptive Constraints:** Extending A6–A8 with thresholds τ , \mathcal{G} , and ϵ that adapt to environmental volatility or meta-learning signals.
- **Computational Instantiation:** Constructing agents that explicitly implement the unified OCOF optimization in non-linear, stochastic, or multi-agent settings.
- **Cross-Domain Generalization:** Evaluating whether coherence under constraint exhibits invariance across domains such as human social dynamics, distributed AI, and hybrid human–machine collectives.

Together, these directions outline a path toward a broader **Operational Theory of General Intelligence**, grounded in the clarity and necessity of OCOF’s axiomatic foundation.

8. Conclusions

OCOF v1.1 establishes a unified account of coherent intelligent behavior grounded in a minimal set of structural and operational axioms. The structural layer (A1–A5) formalizes the representational substrate that governs how information is admitted, differentiated, weighted, and integrated into global state dynamics. The operational layer (A6–A8) introduces the requisite regulatory conditions—reciprocity, geometric feasibility, and temporal coherence—that ensure the stability of

these dynamics over time. Taken together, these components define a jointly constrained system in which coherence is neither presupposed nor externally imposed, but arises as the necessary consequence of simultaneously satisfying the structural boundary conditions and the operational constraints.

By expressing these constraints within a unified divergence-minimization structure, the framework demonstrates that phenomena commonly associated with predictive processing and optimal control emerge endogenously from the interaction of the axioms rather than from adherence to a specific objective function. At the same time, OCOF maintains formal independence from these traditions, offering a substrate-neutral account of coherence that relies on neither teleological aims nor architectural commitments.

The empirical evaluation conducted through the methodological protocol corroborates that the operational axioms impose measurable and falsifiable constraints on behavior: reciprocity stabilizes updating under stochastic coupling; constraint geometry improves feasibility and reduces search space; and temporal coherence mitigates catastrophic divergence. While these results do not constitute a full behavioral validation, they show that the axioms are internally consistent, computationally tractable, and sufficient to support coherent state evolution in simplified agent settings.

The abstract nature of the framework defines its appropriate scope. OCOF v1.1 deliberately avoids specifying concrete learning algorithms, neural substrates, or representational formats. This abstraction preserves generality while leaving the scalability of constraint satisfaction in high-dimensional, non-stationary environments as an open but well-framed challenge. These boundaries constitute scope conditions rather than theoretical shortcomings, clarifying the level of analysis at which the theory is intended to operate.

Several research trajectories follow naturally from this foundation. Adaptive versions of the operational axioms may allow thresholds such as τ , G , and ϵ to vary dynamically with environmental volatility. More complex agent implementations could instantiate the unified optimization structure directly in multi-agent, non-linear, or stochastic environments. Cross-domain validation—from human social cognition to distributed machine systems—may further determine whether coherence under constraint represents a general organizing principle invariant across substrates.

In sum, OCOF v1.1 provides a formally precise, computationally tractable, and theoretically conservative basis for understanding coherent intelligence. By distinguishing structural organization from operational regulation and demonstrating how coherence arises from their joint satisfaction, the framework offers a principled path toward a general operational theory of intelligent behavior.

AI Assistance Statement: Large language models (including ChatGPT and Gemini) were used in the preparation of this manuscript solely for linguistic refinement, formatting assistance, and limited structural proofreading. All conceptual framing, analytical distinctions, theoretical development, and interpretive decisions were generated exclusively by the author. No part of the analysis, argumentation, or claims in this manuscript was autonomously produced by any AI system. The author retains full responsibility for the content of the work.

Appendix A. Notation Summary

This appendix summarizes the core symbols used in the OCOF v1.1 formulation. All notation is substrate-neutral and applies to biological, synthetic, and hybrid cognitive systems.

Symbol – Definition

$\partial\Omega$ – Boundary of admissible information exchange

β – Precision weighting parameter

ΔS – Semantic separation metric

δ – Semantic significance threshold

π – Policy or selection function

Φ – Structural mapping from filtered information and policies to global states

X_t — Global state at time t
 $\Sigma(\text{global})$ — Set of valid global states
 R — Reciprocity measure
 τ — Minimum reciprocity threshold
 G — Feasible geometric manifold (Constraint Geometry)
 \mathbb{D} — Admissible dynamical space
 \mathcal{E}_t — Expected divergence or prediction error
 F — Temporal state transition function
 ε — Allowable temporal deviation
 $\mathbb{I}(\cdot)$ — Indicator function
 $\Psi(\cdot)$ — Penalty function for reciprocity violation
 λ_i — Lagrangian constraint weights
 (All symbols use standard Unicode for cross-platform compatibility.)

Appendix B. Structural Axioms (A1–A5)

A1. Boundary (Existence)

A cognitive system must maintain an information boundary $\partial\Omega$ distinguishing internal from external states.

A2. Precision (Inference)

Incoming information is weighted by a finite precision parameter β , ensuring stable filtering and avoiding singularities.

A3. Semantic Differentiation

Representational updates require $\Delta S > \delta$, guaranteeing meaningful separation between distinct inputs.

A4. Policy and Integration

A policy π selects transitions consistent with the system's representational structure.

A5. Global Coherence

The resulting state must satisfy $X_t \in \Sigma(\text{global})$, ensuring representational non-contradiction. These axioms define the representational substrate on which operational constraints act.

Appendix C. Operational Axioms (A6–A8)

A6. Reciprocity

Bidirectional exchange must satisfy $R \geq \tau$ to ensure stable coupling with the environment or other agents.

A7. Constraint Geometry

Transitions must lie within the feasible manifold

$$G = \{ v \mid C(v) = 0 \},$$

representing physical or logical constraints.

A8. Temporal Coherence

Long-horizon trajectories must satisfy

$$\|X_{(t+1)} - F(X_t)\| \leq \varepsilon,$$

preventing catastrophic divergence.

These operational conditions complete the two-layer system on which OCOF v1.1 is built.

Appendix D. Unified Objective Function

For completeness, the unified divergence-minimization objective is provided below. This expression formalizes how structural and operational constraints converge into a single analyzable formulation.

Minimize:

$$J = \mathcal{E}_t$$

$$\begin{aligned}
& + \lambda_1 \Psi(R) \\
& + \lambda_2 \mathbb{I}(\Delta x \notin G) \\
& + \lambda_3 \|X_{(t+1)} - F(X_t)\|
\end{aligned}$$

References

1. Amari, S. I. (2016). *Information Geometry and Its Applications*. Springer.
2. Barlow, H. B. (1961). Possible principles underlying the transformation of sensory messages. In W. A. Rosenblith (Ed.), *Sensory Communication* (pp. 217–234). MIT Press.
3. Battaglia, P. W., Hamrick, J. B., Bapst, V., Sanchez-Gonzalez, A., Zambaldi, V., Malinowski, M., ... & Pascanu, R. (2018). Relational inductive biases, deep learning, and graph networks. *arXiv preprint arXiv:1806.01261*.
4. Bechhoefer, J. (2021). *Control Theory for Physicists*. Cambridge University Press.
5. Bennett, C. H. (2003). Notes on Landauer's principle, reversible computation, and Maxwell's Demon. *Studies in History and Philosophy of Science Part B: Studies in History and Philosophy of Modern Physics*, 34(3), 501–510.
6. Buckley, C. L., Kim, C. S., McGregor, S., & Seth, A. K. (2017). The free energy principle for action and perception: A mathematical review. *Journal of Mathematical Psychology*, 81, 55–79.
7. Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences*, 36(3), 181–204.
8. Friston, K. (2010). The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience*, 11(2), 127–138.
9. Friston, K., & Parr, T. (2018). Active inference and learning. *Neuroscience & Biobehavioral Reviews*, 68, 862–879.
10. Gibson, J. J. (1979). *The Ecological Approach to Visual Perception*. Houghton Mifflin.
11. Hohwy, J. (2013). *The Predictive Mind*. Oxford University Press.
12. Jaynes, E. T. (1957). Information theory and statistical mechanics. *Physical Review*, 106(4), 620–630.
13. Klyubin, A. S., Polani, D., & Nehaniv, C. L. (2005). Empowerment: A universal agent-centric measure of control. *2005 IEEE Congress on Evolutionary Computation*, 1, 128–135.
14. Koestler, A. (1967). *The Ghost in the Machine*. Hutchinson.
15. Lake, B. M., Ullman, T. D., Tenenbaum, J. B., & Gershman, S. J. (2017). Building machines that learn and think like people. *Behavioral and Brain Sciences*, 40, e253.
16. Landauer, R. (1961). Irreversibility and heat generation in the computing process. *IBM Journal of Research and Development*, 5(3), 183–191.
17. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444.
18. Pezzulo, G., Rigoli, F., & Friston, K. (2018). Hierarchical active inference: A theory of motivated control. *Trends in Cognitive Sciences*, 22(4), 294–306.
19. Russell, S. (2019). *Human Compatible: Artificial Intelligence and the Problem of Control*. Viking.
20. Seth, A. K. (2014). A predictive processing theory of sensorimotor contingencies: Explaining the puzzle of perceptual presence. *Cognitive Neuroscience*, 5(2), 97–118.
21. Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, 27(3), 379–423.
22. Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., ... & Hassabis, D. (2017). Mastering the game of Go without human knowledge. *Nature*, 550(7676), 354–359.
23. Tishby, N., Pereira, F. C., & Bialek, W. (2000). The information bottleneck method. *arXiv preprint physics/0004057*.
24. Wiskott, L., & Sejnowski, T. J. (2002). Slow feature analysis: Unsupervised learning of invariances. *Neural Computation*, 14(4), 715–770.

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